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Hypersoft Sets with Weight-Based SVM for Medical Uncertainty Modeling: A Case Study in Heart Disease Diagnosis

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Abstract

The HyperSoft Set (HSS) is a powerful tool for Multi-Criteria Group Decision-Making (MCGDM) problems because it expands on the concept of the soft set by combining many sets of qualities. The function F in this framework is a multi-argument function. The importance of uncertainty in medical practice is becoming more widely recognized, yet research on this topic remains fragmented across various disciplines. Considering several attributes and their sub-divisions, ambiguity, imprecision, and uncertainty make the Data Mining (DM) complex. The Fuzzy HyperSoft Set (FHSS) combined with the Weight-Based Support Vector Machine (WSVM) algorithm is presented in this study to overcome those complex problems. This study mainly emphasizes detecting critical symptoms to diagnose diseases. Initially, the K-Means Clustering (KMC) algorithm was employed to pre-process the dataset. The noise from the data can be effectively eliminated by this KMC method. This process significantly improved the accuracy of medical Data Classification (DC). This uncertainty became a basic feature of people's lives. Each attribute is attributed to a group of possible objects in the discourse world. The FHSS method uses the Fuzzy Membership (FM) to handle uncertain data. This integration will also support expressing those data in detail, and DM was also enhanced. For medical diagnosis, the WSVM algorithm is then employed. Classification outcomes were improved by employing this WSVM method in a dataset. Experimental outcomes indicate that the suggested FHSS-WSVM algorithm executes better than the current Accuracy, precision, recall, and F-measure methods. The model was evaluated using the Cleveland heart disease dataset, comprising 303 patient records with 13 diagnostic attributes. Comparative analysis is conducted against conventional classifiers such as standard SVM, Random Forest, and fuzzy soft set-based methods. Experimental results demonstrate the superior performance of FHSS-WSVM, achieving 92.3% accuracy, 91.6% precision, 90.8% recall, and an F-measure of 91.1%, outperforming baseline models by statistically significant margins ($p < 0.05$).

Keywords: Medical uncertainty, Healthcare environment, Fuzzy hypersoft set, Weight-based support vector machine.

1 | Introduction

In the evolving area of medical study, the complexity of data often reflects the complexity of the biological systems [1]. For development, effective modeling and analysis of such multifaceted datasets are essential. Soft

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sets and their numerous expansions will pay way for comprehending the complex health claims data analysis realm. Treatments applied, providers involved, billed amounts, and prescriptions delivered were the factors of this data analysis [2]. Despite the inherent uncertainty and uncertainty of healthcare claims data, these mathematical techniques allow for extracting important information. Developments in customized treatment, therapies, and diagnostics are also facilitated.

It expands the awareness regarding the significance of uncertainty in medical practice [3]. Research on this subject is spread across multiple disciplines. There is no single, widely recognized definition for this topic. Concepts from various fields have not been completely unified. The lack of integration among ideas contributes to confusion as different academic areas approach the topic from distinct perspectives. This fragmentation hinders a comprehensive understanding of the subject. A cohesive framework is needed to bridge these diverse viewpoints. Efforts to synthesize research findings are still in the early stages.

There is a lack of comprehensive understanding regarding the normative and interactional issues in complex healthcare settings. So, it cannot effectively address those issues. Through peer exchanges and online resources, along with medical professionals, teenagers and those caring for them are becoming increasingly involved in this growing awareness of uncertainty. This enhanced access to data will enhance patient involvement in Data Mining (DM) [4], [5]. Adolescents' increasing independence might raise questions about their capacity to make wise and well-informed decisions. Thus, involving them in the DM process adds further uncertainty.

It has a wide range of applications in several branches of mathematical research. A novel approximation technique was introduced to address the current models' limitations and incorporate the features of the most relevant current models. Including HSS into SFHSS allows one to handle situations in which membership degrees are not known precisely or in which gradual transitions between membership grades are required.

An extension of conventional Fuzzy Sets (FS) is SFHSS. Spherical functions and HSS are included in SFHSS [6]. One can deal with circumstances where membership grades are not precisely known or when gradual transitions between membership grades are necessary by using HSS into SFHSS. SFHSS has applications in various fields where complexity and uncertainty are common. Image Processing (IP), pattern recognition, DM, expert systems, Machine Learning (ML), and DM were some of its instances. SFHSS can be used to simulate and analyze real-world problems because of its improved representational capabilities. Overall, SFHSS, imprecision, and uncertainty can be utilized to manage complexity in data analysis and modeling [7]. They provide a more adaptable and expressive way to depict data in various situations. The DM and problem-solving skills were also facilitated [8].

Problems with precision in clinical data, ambiguity, and overlapping attribute domains might make it difficult to diagnose accurately in contemporary healthcare systems. Low diagnostic reliability and less-than-ideal decision limits result from using traditional classification models, such as regular Support Vector Machines (SVMs), to handle medical variables, which are multi-granular, correlated, and fuzzy. In addition, modern soft computing methods, including fuzzy soft sets and soft sets, do not have the detailed parameter mapping and hierarchical decomposition required to portray complex clinical situations accurately. An extremely important diagnostic framework is required to precisely represent uncertainty and adaptively maximize classifier performance in the face of such complexity.

Uncertainty and linguistic barriers still affect medical diagnosis and treatment. Patients frequently use ambiguous or inaccurate language when describing their symptoms. It makes it challenging to diagnose their diseases correctly. Inconsistencies might arise from the subjective interpretation of diagnostic criteria. The complicated and unpredictable nature of disease development makes treatment planning more difficult.

Predicting results becomes more difficult because of variations in how patients react to treatments. Inconclusive test results and a lack of clinical data sometimes complicate these challenges. Thus, the need for innovative solutions is highlighted.

In complex healthcare settings, addressing medical uncertainty is considered to be the main objective of this study. Despite several research investigations and approaches, there is still no assurance that medical data classifiers will achieve perfect accuracy. The error rates and classification accuracy were the limitations faced by the current methods. The error rates and classification accuracy can significantly impact healthcare decisions and outcomes. The classification performance can be improved by introducing the algorithm in this study. This algorithm helps to overcome those limitations. The main contributions are using the FSHSS framework, the KMC method for data pre-processing, the WSVM algorithm for classification, and the resolution of medical uncertainty. The recommended method generates more dependable results for the provided benchmark datasets by utilizing these sophisticated algorithms.

The Fuzzy HyperSoft Set (FHSS)-WSVM model stands out from previous FHSS-based models because it aggregates to provide Fuzzy Membership (FM)-driven sample weights. These weights are then integrated into the optimization goal of the SVM. Enhancing boundary accuracy in uncertain choice areas, this connection dynamically modifies the penalty term for each occurrence depending on its diagnostic relevance. Adding a utility-optimized loss function, which balances computing efficiency, error reduction, and diagnostic precision, further differentiates the model. The end product is a powerful hybrid classifier that improves decision separability in ambiguous or overlapping clinical data cases. This feature is underutilized in current FHSS or WSVM implementations and efficiently captures complex attribute interdependencies through hypersoft decomposition.

Research Question as follows:

I. RQ1: How can FHSS be effectively integrated with a Weight-Based Support Vector Machine (WSVM) to model diagnostic uncertainty in medical datasets?

II. RQ2: To what extent does the FHSS-WSVM framework outperform conventional classifiers (e.g., SVM, Random Forest) regarding accuracy, precision, recall, and F-measure in heart disease diagnosis?

III. RQ3: How does the FM-driven weighting mechanism influence the classification performance of WSVM?

IV. RQ4: How does KMC improve data granularity during pre-processing, and how does it impact the overall diagnostic accuracy?

2 | Related Work

In 2024, Saqlain et al. [9] proposed that Neutrosophic-Linguistic Valued HSS (N-LVHS) are instrumental in Decision-Making (DM) processes, as they proficiently handle linguistic uncertainty, represent real-world complexities, and integrate multidimensional information. Language is inherently linked to uncertainty and indeterminacy, serving as a core medium for expressing and conveying information. Linguistic expressions are often characterized by ambiguity, imprecision, and vagueness. Their interpretation is heavily influenced by context, personal perception, and subjective perspectives, leading to potential ambiguities in understanding.

Askari and Motamed [10] suggested an improved fuzzy convolutional neural network for detecting drug dosage in cardiac patients. This article presents a technique for detecting heart disease and prescribing medication dosages for patients based on a fuzzy optimal convolutional neural network that extracts the optimum features. Once PSO has trained the neural network, its weights will be fine-tuned. Both demographic information and Electrocardiogram (ECG) data are used in this paper. Also recommended is a function called medication dosage that recommends the medicine dose depending on the severity of the heart disease diagnosis. By using both the MIT-BIH and UCI databases concurrently, the suggested strategy outperformed competing intelligent methods, achieving a detection accuracy of 95.1%.

In 2022, Rahman et al. [11], using fuzzy parameterized Fuzzy HSS (FHS) with Riesz Summability, this study seek to integrate these characteristics. Developing two distinctive medical diagnostic decision-support algorithms by applying the Riesz mean approach and the Δ-set aggregations after investigating the attributes and aggregations of the Δ-set. A case study using actual characteristics and subattributes from the Cleveland

dataset to diagnose heart disease is then used to verify these algorithms. The appropriate transformation criteria turn real and subattribute values into fuzzy ones. The results obtained from both techniques are reliable and consistent under hypersoft situations. A structural comparison with other previously constructed models is used to analyze the study's favored characteristics to determine flexibility and dependability. This method of detecting heart-related illnesses uses fewer assessing qualities and accompanying sub-value-based tuples, ensuring precise results.

In 2023, Ihsan et al. [12], this approach utilized a multi-argument approximate function capable of transforming sub-characteristic pairs into the power set of the universe. This structure mainly aims to group each attribute into valued groups of sub-characteristics. This vital aspect makes the mathematical valuable framework for managing uncertainties and improves the DM process's adaptability and dependability. Real information from the Cleveland dataset for heart disease is used to assess the reform process' accuracy. To illustrate the benefits of this strategy, a thorough comparison with current approaches is given.

Kikoo et al. [13] introduced the hybrid nonlinear Bayesian-Neural Networks (BNN) approach for an intelligent customer classification model. This study combines practical and exploratory methods by analyzing data from 98,604 clients of one Iranian bank using DM, fuzzy logic, and nonlinear Bayesian model averaging. The consumers were chosen at random from among the banks operating in Iran. Nonlinear Bayesian models (TVP-DMS, TVP-DMA, and Bayesian Model Averaging (BMA)) were used to input 22 customer-related variables in this study. When looking at accuracy based on mistake rate, BMA was the best. According to the findings, account balance, total deposit balance, total current facility balance, and the number of financial transactions were non-fragile variables. The next thing to know is that the C-MEANS method outperformed the K-MEANS method in accuracy. Next, we investigated the features of each of the 16 clusters found using the C-MEANS technique. Consequently, neural network and meta-heuristic models were evaluated using the chosen variables of the Bayesian model averaging technique. The accuracy rating indicated that the BMA model was the most precise.

Saqlain [14] proposed the DM method using VIKOR and Intuitionistic HyperSoft Set (IHSS) for sustainable hydrogen production. The IHSS paradigm evaluated environmental impacts, improved resource allocation, handled uncertainties, and implemented Multi-Criteria Decision-Making (MCDM). The main objective of this study was to solve the mystery of how to choose between several methods of producing hydrogen. A more sustainable energy future is on the horizon, and this strategy paves the way for more eco-friendly hydrogen generation processes.

Rahman [15] suggested the theoretical context for (θ,β)-convexity and (θ,β)-concavity with HSS settings. this article discusses the basic inclusive properties and set-theoretic operations of the standard notions of-convex and-concave sets in an HSS setting. The proposed convex structures are also subjected to the conventional ideas of the first and second senses of convexity to provide results that are more generally applicable when dealing with ambiguity.

Choudhary et al. [16] proposed the Spherical Hesitant Fuzzy Soft Yager aggregation data (SHFSS) for improved industrial control systems of DM. The study expands upon Yager's parametric families of t-norms and t-conforms to examine these collections. This method is crucial for fixing Multi-Attribute Decision-Making (MADM) issues regarding ICS security. To achieve this goal, four separate Aggregation Operators (AO) are suggested: Geo-weighted averaging aggregation, ordered weighted averaging aggregation, weighted fuzzy soft yager, and geo-ordered weighted geometric aggregations.

Mehmood et al. [17] recommended the entropy and similarity measures and their few applications because of vague soft sets. Two important measuring methods are the subject of this paper. Vulgar soft sets about sharp points in space present these methods. Pertinent instances back all of these tactics.

Sezgin et al. [18] discussed the In-depth analysis of limited and extended lambda operations for soft sets. The results of this study show that considering the distribution rules and algebraic properties of the extended lambda operation, it forms various important algebraic structures like semirings and near semirings in the

universe-wide collection of soft sets. The theory's central tenet, the operations of soft sets, forms the basis for many applications, such as cryptology and DM procedures, making this theoretical study theoretically and pragmatically crucial.

Sezgin and İlgin [19] introduced the soft intersection, almost bi-quasi ideals of semigroups. Contrary to the notion of soft intersection ideals, we prove that any soft intersection nearly bi-quasi-ideal is both a soft intersection nearly ideal and a soft intersection nearly bi-ideal. In addition, we prove that for any idempotent soft intersections around bi-quasi ideals, there exists a soft intersection around subsemigroup, a soft intersection around the weak interior ideal, a soft intersection nearly tri-ideal, and a soft intersection almost tri-bi-ideal.

Onoja et al. [20] presented pattern recognition and disease diagnosis using weighted intuitionistic fuzzy distance metrics. Furthermore, using the new weighted intuitionistic fuzzy distance metric, a pattern identification issue is discussed to determine the most closely related to an unknown pattern. Furthermore, medical diagnosis uses the novel weighted intuitionistic fuzzy distance metric to determine the underlying medical issue based on symptoms. Lastly, when compared to the current intuitionistic fuzzy distance measures, the newly constructed weighted intuitionistic fuzzy distance measure is shown to be better.

Sezgin and Çam [21] developed a new product for soft sets with its DM. Moreover, the author studies the interrelationships of this product with other soft set operations by looking at the distributions of soft plus products across different functions. Finally, an example is provided to show how the approach may be used effectively in various contexts employing the int-uni operator and the int-uni decision function for the soft plus-product of the int-uni DM algorithm, which selects an optimum collection of components from the available options.

Chandel [22] deliberated on the healthcare chatbot using SVM & Decision Tree. By providing a user-friendly platform that simulates conversations with a real healthcare practitioner, the chatbot hopes to facilitate communication between patients and their physicians. Through ML methods, the chatbot can categorize symptoms, provide medical advice, and suggest further medical consultations as needed. Based on input data, the decision tree algorithm forecasts illnesses and proposes treatment pathways, while the SVM model classifies symptoms to detect possible health concerns. The system was evaluated using real-world healthcare datasets to guarantee precise illness prediction and efficient user engagement. The experimental findings show that the chatbot outperforms conventional rule-based systems by a wide margin regarding illness prediction.

Uluçay and Şahin [23] examined the Intuitionistic Fuzzy Soft (IFS) Expert Graphs with Application. The shortcomings of the theories' parameterization tools are the root cause of the problems. Soft set theory is more versatile because of its parameterization tools. This article defines and discusses IFS expert graphs, their union, and their intersection. The novel idea is an MCDM approach based on IFS experts and graphs.

Vijayabalaji et al. [24] investigated the Soft expert method in the rough FS and its application in the MCDM issue. This hypothesis has certain limitations when explaining expert opinion, even if it seems nice in principle. A "soft expert set" concept was being worked out to resolve this problem. Theoretically, this study seeks to interrelate rough FS with soft expert sets. A straightforward method for handling DM situations using the soft expert rough fuzzy set models is provided.

Murugan et al. [25] analyzed the Large Language Models (LLM) and blockchain for secure data management in psychiatry. While protecting patient privacy, the LLM offers in-depth clinical analytics for individualized mental health treatments by sifting through large amounts of unstructured data. Secure and restricted access to confidential mental health information are both made possible by blockchain technology's decentralized storage, immutability, and data integrity features. Secure, efficient, and privacy-preserving mental data management, better clinical DM, and patient trust preservation will result from integrating technology.

Zheng et al. [26] suggested fuzzy Deep Learning (DL) for uncertain medical data. Some novel ideas are presented in this piece: it first proposes four distinct frameworks for using fuzzy DL models on ambiguous medical information. The author looks closely at seven different fuzzy DL models, five kinds of uncertain

medical data, and five application situations. This critical analysis of fuzzy DL for ambiguous medical information highlights its benefits, drawbacks, and potential future research paths, and it offers helpful recommendations for more in-depth study.

Manoharan and Edalatpanah [27] proposed evolutionary bioinformatics with a veiled biological database for healthcare operations. GACO combines genetic and ant colony optimization techniques to carry out the optimization scenario. Five different situations were used in the trials to determine how well the suggested design worked. It has been shown that the suggested method can process healthcare bioinformatics data in real time with a service quality of 95%.

Yan et al. [28] recommended fuzzy clustering and battle royale optimization for disease diagnosis systems for smart healthcare. EMRs are supplemented with missing data using a self-organizing fuzzy logic classifier, and outliers are detected using fuzzy clustering based on the forest optimization technique. After that, we devise a feature selection method that uses the battle royale optimization algorithm to weed out unnecessary details and find the best EMR features. An eigenvalue-based ML technique is utilized to classify the fused and refined data further to ascertain whether a patient displays a certain ailment. To test how well the suggested method works, the author runs simulation tests using popular datasets on diabetes and heart disease and utilizes metrics like F-measure, recall, accuracy, and precision to see how well it does.

Zulqarnain et al. [29] discussed the Interval-Valued Pythagorean Fuzzy HSS (IVPFHSS) for fair bed distribution during the COVID-19 pandemic utilizing the TOPSIS based on correlation coefficients. During the epidemic, the method is used to address the issue of how to distribute hospital beds best. The significance of utilizing correlation measures for DM in complicated and unpredictable settings, such as the COVID-19 pandemic, is shown by this research. A powerful and critically important MADM approach. A biogeographically informed dynamic bed allocation algorithm will be enhanced to realize the optimal DM framework. Numerical studies can provide sensitivity evaluations and discuss optimal decision structures.

Jayakumar et al. [30] deliberated the healthcare supplier selection based on enhanced MADM with Lq* q-Rung orthopair multi-fuzzy soft sets. A MADM scenario demonstrates the suggested Lq* qROMFSS's usefulness in healthcare supply chain management and emphasizes its importance.

Surya et al. [31] presented the Entropy for q-rung linear diophantine FHS with its application in MADM. This article presents a MADM algorithm that is based on recommended entropy. It includes a numerical example of choosing an appropriate wastewater treatment method to show how effective the algorithm is in real-life scenarios. This comparison analysis explains the suggested algorithm's and ideas' validity, robustness, and superiority by analyzing the pros and cons of current theories and algorithms.

Shitharth et al. [32] introduced the computational blockchain process with offloading analysis to enhance security using federated learning optimization. The suggested method's main strength is its use of a blockchain-based offloading methodology for data processing, which guarantees the utmost confidentiality for all data. The use of data weights in load balancing, together with parametric assessments performed in real-time to ascertain the consistency of every data monitored with IoT, is a result of a problem approach built concerning clusters. Results from the five-scenario procedure show that offloading analysis with blockchain is more secure, increasing data processing accuracy for all IoT applications by 89%.

Gurmani et al. [33] developed the extension of the TOPSIS under the q-rung orthopair fuzzy hypersoft environment based on the correlation coefficient and its application to multi-attribute group DM. Using the q-rung ortho-pair FHS settings, the author created a correlation coefficient-based TOPSIS method after introducing correlation and weighted correlation coefficients and discussing a few properties. A DM approach is suggested for handling uncertain and ambiguous information using the TOPSIS method in a q-rung ortho-pair FHS setting.

Musa [34] offered the N-bipolar HSS for improving DM algorithms. Unlike traditional binary BHS sets and continuous fuzzy BHS sets, the N-BHS set offers a parameterized universe representation, which allows for

a limited level of detail in perceiving qualities. Second, when dealing with multi-argument approximations, this model represents a new field of study that seeks to overcome the shortcomings of the N-bipolar soft set. The N-BHS set is a potent instrument for solving uncertainty-related issues because it strategically divides attributes into separate subattribute values utilizing separate sets. The work defines many algebraic concepts to achieve these goals; for example, BHS sets generated from a threshold, equivalence under normalization, normalized N-BHS sets, effective N-BHS sets, incomplete N-BHS sets, and N-BHS accompaniments.

Wanke et al. [35] suggested the unbiased MCDM score decompositions into latent vagueness and randomness elements for performance assessment and lockdown decisions of the UK healthcare system in dealing with COVID-19. The evaluation results are analyzed using a three-step MCDM method. The first step is to use software like TOPSIS or Complex Proportional Assessment (COPRAS) to calculate partial distances or utility functions.

Secondly, the Latent Vagueness and Randomness Components (LAVRA) approach removes uncertain components from unbiased performance ratings. Third, drivers of lockdowns are categorized using performance, fatalities, and areas employing a bootstrapped neural network regression. The availability of ventilated beds is a crucial motivator, but staff absenteeism from COVID-19 and a high admission rate of senior inpatients are less significant. According to the data, TOPSIS yields performance scores between 0.65 and 0.75; however, COPRAS analysis considerably lowers the ratings.

Sarkar et al. [36] proposed the Sugeno–Weber triangular norm-based aggregation operator under T-Spherical Fuzzy Hypersoft (T-SFHSS) context. For decisions using data that is not crystal clear, the T-SFHSS is the way to go. The "intuitionistic FHS" and the "Pythagorean FHS" are two examples of FSs that the T-SFHSS improves. The goal is to make fuzzy set computations more accurate. The author provides new operational guidelines for T-Spherical Fuzzy Hypersoft Numbers (T-SFHSNs) based on the Sugeno-Weber t-conorm and t-norm to aggregate the decision data efficiently. Considering these operational principles, we suggest several T-SFHS AO that exhibit favorable features. To prove the practicality and efficacy of the current approach, we do a case study on natural agribusiness.

Sharma et al. [37] recommended the T-SFHSS structures to identify suitable hydrogen power plant locations. Additionally, the algebraic characteristics of certain common matrix operations have been investigated. The supplied criteria were used to computationally study the locations for selecting hydrogen power plants using the offered unique methods. An illustrated example is also provided. The author has included a comparative analysis and a comparison table, benefits, and a discussion of the suggested algorithms' and their implementations' effectiveness.

Demir and Moslem [38] suggested fuzzy MCDM for improving the management of medical waste produced during the pandemic. The author may arrive at a final ranking by combining expert views using the mean operator, evaluating criteria using the ranking alternatives using the fuzzy compromise ranking and fuzzy preference selection index from distance to ideal solution technique. The social component is the most important, with a weight of 0.3217, according to the weightings. The most important metric is disinfection efficiency, which weighs 0.0823. With a utility function value of 5.4579, the autoclave is deemed the best disposal technology. Sensitivity studies confirmed the robustness and consistency of the models.

Zulqarnain et al. [39] offered the IVPFHSS with Their Application to resolve the MCDM issue. Compared to the current interval-valued Pythagorean fuzzy soft set, the IVPFHSS handles ambiguous and uncertain data well. Undoubtedly, it is the gold standard for enhancing DM-related fuzzy data. The IVPFHSS has certain suggested operating laws. The integral value-preserving IVPFHS weighted average IVPFHSWA and the integral value-preserving IVPFHS Weighted Geometric (IVPFHSWG) operators have been defined as two novel AOs based on the provided operational rules. When dealing with the challenges of material selection in industrial company contracts, MCGDM plays an active role.

Zulqarnain et al. [40] recommended the Intuitionistic Fuzzy HSS (IFHSNs) with their application to solve the MCDM issue. The basic characteristics of two AOs, the IFHSWG and the IFHS Weighted Average

(IFHSWA) have been described, both of which are based on operational rules that have been created. The author has also constructed a DM strategy that uses the AOs we have developed. Sustainable Supply Chain Management (SSCM) uses the existing method to present a method for resolving DM issues related to sustainable supplier selection.

Zulqarnain et al. [41] discussed the fundamental operation of Interval-Valued Neutrosophic HSS (IVNHSS) with their possessions. The objective of this work is to provide a foundational extension of IVNHSS. Along with the desired qualities of IVNHSS, the author created some fundamental operations such as addition, union, intersection, truth-favorite, difference, False-favorite, etc.

An important need in the existing medical diagnostic methods is filled by the proposed FHSS-WSVM framework, which provides a solid answer to the problem of how to describe the uncertainty and attribute interdependencies prevalent in large clinical datasets. Integrating FHS with a weight-based SVM delivers a new approach to uncertainty-aware learning, particularly useful in precision diagnostics, where high levels of interpretability, flexibility, and accuracy are required even in the face of ambiguity. This study takes a step forward in methodology by training SVMs using expert-driven fuzzy weight propagation, which goes beyond the capabilities of traditional ML and soft computing models. The improvement of diagnostic decision reliability and the preservation of computational tractability are its key contributions.

3 | Proposed Method

This work proposes FHSS with WSVM algorithm to enhance the medical uncertainty in complex healthcare environments. Employing uncertainty in healthcare data, the FHSS-WSVM framework aims to improve prediction accuracy, patient outcomes, and clinical DM, thereby changing standard approaches to healthcare environments.

3.1 | Addressing Medical Uncertainty in Complex Healthcare Environments

This study focuses on identifying diseases in patients based on key symptoms. Suppose that n illnesses exist and that each disease has m symptoms. Certain diseases are challenging to diagnose when a patient has almost all these symptoms. The WSVM algorithm, when used with the HSS, resolves this ambiguity by precisely identifying the patient's medical state and determining the necessary diagnosis.

Uncertainty is fundamental to human existence and a central challenge in medicine. It is a shared issue encountered by every patient receiving healthcare, every doctor providing it, and the administrators, payers, policymakers, and researchers convoluted in delivering, financing, regulating, and studying healthcare. Across all these roles, uncertainty manifests in different forms, originating from multiple sources concerning relevant issues and shaped through communication. This uncertainty prompts action and elicits various responses from other stakeholders.

Modal verbs (May, can), modal adverbs (Maybe, possibly), and assertions of incomplete knowledge (I do not know, I suppose, ambiguous formulations) are examples of "uncertainty displays," which might present themselves in interactions. The statement "Puberty blockers may lessen gender dysphoria, but we don't know their precise impact on bone density" is one example of how a healthcare professional could emphasize the unpredictability of future results in the context of adolescent transgender care. This type of phrase expresses ambiguity, making it a real problem that must be resolved immediately.

In another way, expressing doubt impacts the encounter and does not always indicate that the speaker lacks particular data [42]. For instance, the uncertainty expresses "I don't know," which does more than communicate knowledge. "I don't know" may be used to create a neutral position and avoid clear agreement or disagreement with the preceding speaker.

Additionally, it may oppose a certain line of inquiry or an interlocutor's (Institutional) objective. The expression "I do not know" might also give the speaker additional time to reflect, organize, or control their

role or place in the discussion. Being ambiguous in descriptions, such as providing evasive or unclear answers on a delicate subject, is another instance of an uncertainty display with an interactional effect.

Secondly, uncertainty develops into an interaction when an unknown circumstance or problem leads to certain interactional actions. For example, healthcare providers may offer further explanations when dealing with uncertain information, helping patients discuss the uncertainty [43]. Significantly, the interactional resources used by each participant influence the interaction's result, such as a decision or consensus on a certain issue. The degree of confidence or ambiguity about a genetic diagnosis, for example, was shown to be strongly impacted by the questions and answers parents provided during genetic counseling. What interactional strategies can teens, caregivers, and medical professionals use to deal with (Moral) ambiguity in transgender care, particularly when making decisions, is placed into question by this?

The membership function, denoted as $\mu(x)$, is the function that gives a number to each element x in the input space. An input value is mapped to its membership values using the membership functions. The membership function of x, to put it more simply, indicates the extent to which it belongs to a fuzzy set. The membership function's values have to be between 0 and 1.

The complexity of medical practice arises from insufficient, unclear, and contradictory information. This complexity has reportedly grown since the 19th century with the advent of modern medicine and throughout the 20th century with the rapid advancement of diagnostic techniques and therapeutic approaches. This complexity is also thought to have been increased by advancements in digital information processing. Other clustering algorithms, such as Hierarchical Agglomerative Clustering (HAC) and DBSCAN, were investigated during the model design phase.

Nonetheless, the deciding factors in its selection were computational efficiency, scalability, compatibility with KMC, and the succeeding FHSS-WSVM pipeline's similarity assumptions based on geometry. Although DBSCAN can handle noise and find non-convex clusters, it wasn't the best fit for this situation since it became unstable when using the Cleveland dataset's small and low-density structure because it was so sensitive to parameter selection (ε and MinPts).

Physicians assess patient risk using subjective factors and/or additional situational knowledge. In the technological age, nearly all physicians rely on information systems during the diagnostic process. These systems either assist in data recording or support DM. However, the vast volume and variety of data, including textual, numerical, and time-series information, increase the complexity and uncertainty of the DM process. Specialized techniques are needed to deal with this unpredictability.

The following categories may be used to group the causes of uncertainty:

I. Patient-related information.

II. The patient's and/or their family's erratic and subjective medical history.

III. While physicians generally gather objective data through physical exams, there may be instances where distinguishing between normal and pathological conditions is unclear.

IV. Laboratory and diagnostic test results can be affected by errors or improper patient behavior before the examination.

V. Patients may simulate, exaggerate, understate symptoms, or omit some entirely.

VI. Physicians highlight the paradox between the absence of a natural categorization system and an increasing number of mental illnesses.

VII. When using a categorical diagnostic system, classification issues might develop in important circumstances.

VIII. The symptoms of patients are often ambiguous, with many potential causes.

IX. Patients struggle to express their condition precisely in mathematical terms, often using vague or ambiguous language.

X. Doctors with varying backgrounds and experiences may interpret information differently.

XI. Pathological conditions often present ambiguous symptoms that resemble those of other illnesses.

Fig. 1. Healthcare uncertainty may come from various sources, including measurement variability, missing or incomplete data, medical diagnostic ambiguity, and treatment uncertainty.

Fig. 1 shows the different sources of uncertainty possibilities in healthcare. This section employs the medical diagnostic technique to detect cardiac issues using actual data from the Cleveland data set in the FHSS environment.

Operational role of selected attributes

Age: Heart disease is also associated with aging. Age-related increases in the risk of heart disease, particularly in individuals aged 60 and above; younger people may also be at risk when other factors are present. Medical experts have divided aging into four stages: 20 years, 40 years, 60 years, and more than 60.

Chest pain type: A major cause for patients to attend the emergency department is chest discomfort, and its characteristics can vary from person to person. It can differ in quality, intensity, duration, and location. The pain may be sharp and intense or dull and aching. While it could indicate a serious heart issue, there are many common, non-threatening causes as well. Angina, non-anginal discomfort, TA, and asymptomatic chest pain are the four basic types of heart-related chest pain. Classic angina symptoms: 1) substernal chest pain that, 2) intensifies with exercise or stress, and 3) improves with rest or nitroglycerin. Two of these conditions must be satisfied for angina to be considered atypical. Hospitalized individuals without acute coronary syndrome or coronary ischemia symptoms are treated with non-anginal pain. Asymptomatic refers to the absence of symptoms for the condition being evaluated [44].

Resting blood pressure: Blood pressure is the force that blood exerts on the artery walls. Two forms of this pressure are distinguished: Diastolic and systolic. The heart experiences diastolic pressure when calm and systolic pressure when it pumps blood into the arteries. Elevated resistance in the arteries may cause hypertension, which is defined as blood pressure that is too high during either the heart's contraction or relaxation phases. The units of measurement for both types of pressure are millimeters of mercury (mm Hg). The blood pressure is normal if the systolic and diastolic blood pressure readings are less than 120 and 80, respectively. A systolic value of 120–129 and a diastolic reading of less than 80 are considered elevated blood pressure.

Serum cholesterol: Cholesterol is a lipid, or form of fat, that passes through the circulation as small fragments covered with proteins. We refer to these mixtures of fat and protein as lipoproteins. The main lipoprotein types in the blood are Low-Density Lipoprotein (LDL), commonly referred to as "bad" cholesterol, and High-

Density Lipoprotein (HDL), sometimes defined as "good" cholesterol. The blood also contains triglycerides, a third type of lipids. We may determine our total blood cholesterol, or serum cholesterol, by testing our LDL, HDL, and triglycerides. Although high cholesterol might increase the risk of heart disease, it is necessary to develop healthy cells. Fatty deposits in the blood vessels caused by high cholesterol have the potential to enlarge over time and obstruct blood flow via the arteries. Serum cholesterol is determined by adding HDL and LDL cholesterol levels and 20% of the triglyceride level. These concentrations might vary between 126 and 564 mg/dL.

Fasting blood sugar: Heart disease patients often raise blood glucose levels due to the "stress reaction." Accordingly, elevated blood sugar may occur in people without diabetes. A healthy individual's blood glucose levels should be within the normal 120 mg/dL range.

Maximum heart rate attained: Heart rate significantly influences oxygen consumption in individuals with ischemic heart disease. Between 71 to 195 beats per minute is the maximum heart rate that may be attained.

Oldpeak and slope: A reliable ECG sign for identifying obstructive coronary diseases is ST depression (S = shock, T = toxicity), which is seen during exercise as opposed to rest. It typically ranges between 0.0 and 0.5 and is measured in millimeters. There are three different slopes for the peak workout ST segment: downsloping, flat (Horizontal), and upsloping.

Thal: Reversible defects (Value = 7), fixed defects (Value = 3, when blood flow is reduced in certain cardiac areas), null (Value = 0), and usual blood flow (Value = 6) are the different forms of thalassemia. Heart problems are usually diagnosed by excluding the null group.

3.2 | Pre-Processing Using K-Means Clustering Algorithm

This study uses the KMC method for pre-processing to enhance database disease diagnosis. Medical uncertainty datasets are applied in this research. The number of symptoms associated with the diseases related to the given medical datasets. The main reasons for selecting KMC were its compatibility with the following fuzzy partitioning in the FHSS framework, computing efficiency, and scalability with high-dimensional medical data.

Although DBSCAN and similar algorithms have their benefits in controlling noise and forming density-based clusters, they are sensitive to parameter choices like ε and MinPts and may produce inconsistent clusters when data distributions differ across dimensions.

While FHSS necessitates attribute decomposition, K-means guarantees deterministic cluster centroids that successfully align with it, resulting in consistent granule creation and decreased pre-processing complexity. KMC is an effective clustering method that groups comparable information derived from the clusters' initial centroids [45].

The cluster centroids are calculated using Euclidean distance. After randomly dividing the data, the process iteratively updates the cluster centers, and each data point is reassigned to the cluster with the closest center. The process concludes when no further reassignment occurs.

The sum of squared differences between the data points and their respective cluster centers is known as the intra-cluster variance, which is minimized using this method. In particular, it means that the intra-cluster variance is reduced more effectively. *Fig. 2* illustrates the KMC algorithm.

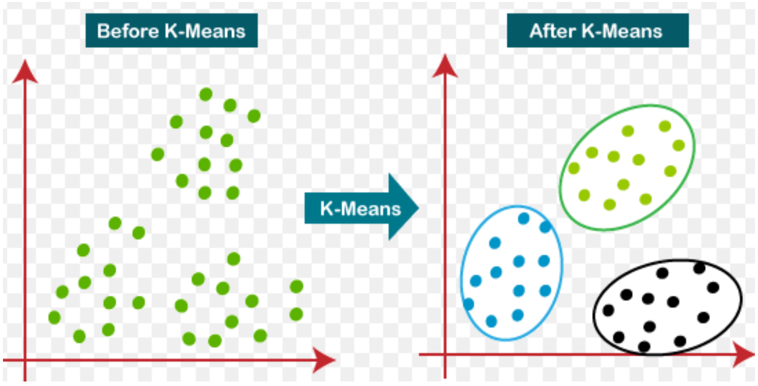

Fig. 2. Example of KMC algorithm.

$$d(i,j) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}, \quad (1)$$

where two points are represented by x_i and y_i in Euclidean n-space in above *Eq. (1).*

Algorithm 1. KMC algorithm for pre-processing.

Select k clusters (D) from the medical uncertainty datasets
Initialize the cluster centers as μ1, …, μk
Set the initial cluster centers to these positions using k data points
Assign random points to the clusters and then calculate the mean of each cluster
Use the distance measure to find the nearest cluster center for each data point and identify the missing values using Eq. (1)
Designate the cluster as the uncertainty of the data point
Determine the cluster centers again
Find any errors or missing numbers and eliminate them
When there are no more reassignments,
stop

The database does not include instances that have missing characteristics. There are two subsets of the database: One with full examples with no missing values and another with incomplete cases that include data gaps. Clusters of complete instances are created when the set of complete instances is subjected to KMC. Each incomplete instance is evaluated individually to fill in the missing attributes with possible values.

After applying KMC to the database and generating clusters, the newly added instance is examined to ensure it has been assigned to the appropriate class. The assigned value is finalized if the instance is correctly clustered, and the process continues with the next instance. If the instance belongs to the incorrect cluster, possible values are assigned and compared to find the proper value. The KMC algorithm is used during the pre-processing stage to improve the accuracy of illness categorization.

HSS provides a multi-attribute decomposition whereby every parameter is refined into sub-parameter tuples, allowing for greater granularity in decision representation. This contrasts traditional Soft Sets that consider a one-to-one mapping between parameters and object characteristics. To address the interdependencies and overlapping medical conditions often seen in clinical datasets, the FHSS framework employs hierarchical attribute decomposition with multi-valued mapping functions. Better uncertainty and attribute correlation modeling are now possible thanks to this upgrade.

3.3 | Hybrid Fuzzy HyperSoft Set with Weight-Based Support Vector Machine for Medical Uncertainty

In this work, a collection of potential pieces from the discourse universe is connected to each property; FHSS provides a versatile framework for representing ambiguous or undefined data. This framework supports several computing activities, including data analysis, pattern identification, and DM, by making it possible to manipulate and show uncertain data completely [46].

By extending the mapping function to include many qualities, changing from soft sets to HSS (HS Set) marks a substantial advancement in modeling complex connections. DM becomes challenging due to the environment's ambiguous, imprecise, and uncertain nature, especially when multiple attributes are involved and further divided. The HSS concept has been utilized to tackle these complex issues.

First, mapping function F is converted into multi-attribute functions to expand the soft set notion to HSS. This change makes the representation of intricate interactions between components inside the discourse world possible.

Consider n distinct attributes, denoted as $\mathrm{a1, a2, \dots, an,}$ for $\mathrm{n} \geq 1$. A set of attribute values, represented in *Eq. (2)* by the letters A1, A2,…, and An, correspond to each attribute. If i and j are in {1,2,…,n}, Ai ∩ Aj = Φ. A HSS over U is represented by the mapping function F, which is defined on the Cartesian product of attribute sets A1 × A2 × … × An.

$$\mathrm{F: A1 \times A2 \times \dots \times An \rightarrow P(U), is\ called\ a \rightarrow P(U).} \tag{2}$$

It indicates a matching subset of items from U for each attribute value combination.

In the discourse world, the concepts of HSS make it possible to analyze intricate connections and interactions between various qualities. This addition makes the in-depth modeling and analysis of complex systems in various domains and applications possible.

Let a1 stand for diagnosis, a2 for treatment, a3 for cost, and a4 for duration, and their corresponding values: A1 = {diabetes, heart problem, respiratory issue}; A2 = {medication, surgery, therapy}; A3 = {low, medium, high}; and A4 = {short-term, medium-term, long-term} are the diagnosis and treatment, respectively. Let $\mathrm{F: A1 \times A2 \times A3 \times A4 \rightarrow P(U)}$ be the function.

Diabetes is diagnosed in both Claims 1 and 2, and both have low costs, short-term duration, and medication treatment (F({diabetes, medication, low, short-term}) = {Claim1, Claim2}). By adding hyperparameters that capture complex links and interactions within healthcare claims data, the HSS expands on the basic concepts of soft sets. The HSS improves the precision and data analysis reliability interpretation in the healthcare industry by including these hyperparameters, which may provide uncertainty and a more complete representation.

Fuzzy-valued HSS aims to enhance the precision and efficacy of medical DM and treatment strategies. These models help healthcare providers manage linguistic uncertainty, represent complex medical data accurately, and incorporate various types of uncertainty [47]. Consequently, these frameworks are vital in improving diagnosis accuracy and developing individualized treatment programs [48]. However, it is not able to classify the disease more accurately.

Hence, this study integrated the WSVM technique with FHSS to classify better given medical uncertainty datasets. Searching for a linear separation hyperplane with the maximum margin for separating data in a higher dimensional space is the goal of this efficient method for medical Data Classification (DC) [49]. The training duration of the standard SVM method is lengthy. Hence, WSVM is offered as a solution to the problem.

The WSVM attains a separation level that is almost optimal in terms of class separation. Information could be detached with nonlinear rules and separated via geometry and linear algebra in the high-dimensional feature space into which WSVM automatically embeds information. It optimizes the distance of either class from its

hyperplane and utilizes the hyperplane for separating the most significant percentage of training information on a similar class [50].

WSVM uses several kernel functions that enable inner products directly in feature space. The WSVM is trained to execute dataset classification utilizing the obtained attributes in this work. Generally, the WSVM creates a hyperplane to divide the high-dimensional space. The training dataset model is used in the testing procedure. With more information, WSVM classifiers, also known as maximal margin hyperplane classifiers, show strong classification outcomes for training sets. The SVM algorithm's structure is depicted in *Fig. 3*.

The proposed FHSS-WSVM model uses a SVM structure as its last classification layer. After pre-processing, this layer is responsible for diagnostic DC using FHSS mapping and weighted attribute optimization. The SVM builds an ideal hyperplane that divides transformed input vectors with the maximum margin to guarantee strong decision boundaries.

This structure differs from conventional SVMs in that weighted feature vectors produced by the FHSS module are used. The importance of each feature in the diagnostic setting determines how much weight to give it. Due to these weights, the classifier can prioritize clinically significant traits and downplay irrelevant variants, impacting margin formation and supporting vector selection.

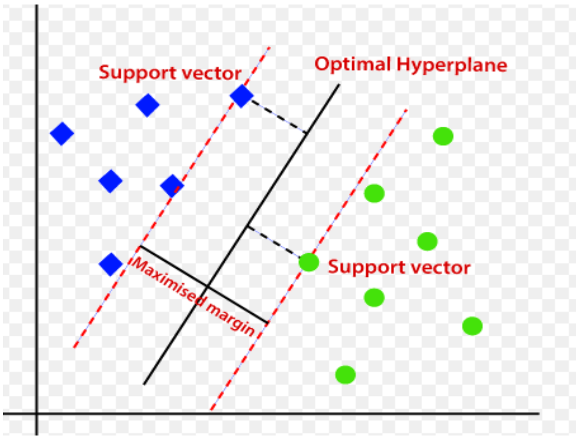

Fig. 3. Structure of SVM algorithm.

The fundamental principle of WSVM is to provide every data point a unique weight according to the significance in the class, such that various data points contribute in a different way to the decision surface's learning. Assuming that the weights are assigned, the training dataset turns into *Eq. (3)* below:

$$\{(x_i, y_i, W_i)\}_{i=1}^{l}, x_i \epsilon R^N, \quad y_i \epsilon\{-1, 1), W_i \epsilon R. \tag{3}$$

Here, the scalar $0 \leq Wi \leq 1$ is the weight allocated to the data point x_i.

The WSVM seeks to improve the margin of separation and lessen the classification error, accuracy, and time to obtain strong generalization ability, beginning with developing a cost function. All training data points are given the same weight (C) throughout the training process, and WSVM uses a penalty term to balance out the impact of less significant data points. The issue of limited optimization is expressed as *Eq. (4)*.

$$\text{Minimize } \Phi(w) = \frac{1}{2} w^T w + ATE \sum_{i=1}^{l} W_i \xi_i, \tag{4}$$

where A is accuracy, T is time, and E is error rate

$$\sum W_i\, \varepsilon_i \cdot U(A, T, E) = \sum W_i\, \varepsilon_i \cdot (\alpha \cdot A - \beta \cdot E - \gamma \cdot T), \tag{5}$$

$\mathrm{s.t.}$

$$\begin{aligned} y_i(\langle w, \emptyset(x_i)\rangle) + b \geq 1 - \xi_i, \quad & i = 1, \ldots . l, \\ \xi_i \geq 0, \quad & i = 1, \ldots . l. \end{aligned}$$

In the formulation above, *Eq. (5)* gives the data point x_i in the W_i weight. Thus, the two-fold formulation turns into

$$W(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{l}\left(a_i a_j t_i t_j e_i e_j\right), \tag{6}$$

$\mathrm{s.t.}$

The upper bounds of α_i SVM are constrained by a constant, whereas in WSVM, they are constrained by dynamical boundaries represented by weight values cteWi. With the help of SVM weight values, it focuses on comprehending the pattern of infected symptoms and efficiently enhances the disease by identifying accurate early-stage features. Healthcare forecasting turned out to be even more precise and complete due to *Eq. (6)* because it allows proper integration of fuzzy data. Extreme skewness in weights harmed generalization, especially on recall and F-measure metrics, whereas moderate alterations in the weight distribution caused little changes in classification accuracy (±1.3%). While demonstrating the model's resilience to mild weight fluctuations, these results confirm that well-calibrated fuzzy weights improve class separability.

$$\propto_2 \mathrm{D}: (2, \mathrm{vfe}): \omega\rho < \alpha + \mu\pi'' > +Za''. \tag{7}$$

The FHSS-WSVM framework $\omega\rho$ is used to determine the weighting of fuzzy components $(2, \mathrm{vfe})$ and decision factors $(\propto_2 \mathrm{D})$ in *Eq. (7)*. It is focused dynamically on improving uncertainty models. Accounts must make different degrees of uncertainty to make healthcare analytics more robust.

$$\mathrm{R} \rightarrow (\mathrm{Wxs_w} + \delta < \mathrm{Ut}'' - \mathrm{Wa}'' >): \mathrm{Vx}' - \mathrm{Rf} < \mathrm{F} - \mathrm{wq}'' >. \tag{8}$$

Within R the FHSS-WSVM framework, the *Eq. (4)* shows how weighted fuzzy information $(\mathrm{Wxs_w})$ is transformed into actionable predictive variables $\mathrm{Vx}' - \mathrm{Rf}\,()$ in *Eq. (8)*. The process by which hypersoft factors $(\mathrm{F} - \mathrm{wq}'')$ refine and alter unclear patient data to increase the accuracy of medical dataset classification. It is important to handle data that optimizes WSVM results so that healthcare analytics are done much better. *Fig. 4* shows the proposed system's overall block diagram.

Specifically, the Δ-set aggregation represents the composite decision structure derived from the HSS layer, capturing the attribute-level granularity through fuzzy partitioned mappings. The notation $\mathrm{R} \rightarrow (\,\mathrm{W_{x_{s\omega}}} + \delta\,)$ has now been clarified: R denotes the FHSS-based relation matrix, $\mathrm{W_{x_{s\omega}}}$ represents the weighted instance vector incorporating FM-driven scaling, and δ is the regularization bias introduced to ensure convergence stability in WSVM optimization.

A FM value is assigned to each data point, which indicates the extent to which it belongs to a certain diagnostic class according to the granularity and partitioning of its attributes. The SVM goal function incorporates these membership values, which are transferred to sample weights, and modifies the penalty term for misclassification.

One way to deal with uncertainty and noise in diagnostic qualities is to use membership values. Higher memberships make samples more influential in establishing the hyperplane, whereas lower memberships make samples less influential. With the clinical importance determined by FHSS-driven fuzzy quantification, the weighted SVM adjusts the margin construction and support vector selection accordingly.

Algorithm 2. WSVM for medical uncertainty.

```
Begin
{
Obtain the input samples.
Apply WSVM training and testing process.
Create fuzzy HSS ();
Apply equation (7) and (8)
Create FHSS (f1, f2, fx) using membership function
For each input fuzzy set
Evaluate Median Fi;
{
Perform Median Fi: Median value of range in fuzzy fi;
Input for WSVM classifier assigned from fuzzy se
Train WSVM ();
 {Train SVM using medical dataset}
Find the medical uncertainty
Select the best features via FHSS
Do {
Find the disease
Check the symptoms for both datasets
Compute classifier accuracy using (4) and (6)
Return higher classification results of medical uncertainty datasets
}
}
Stop
```

The FM function $\mu(x)$ is defined to map each diagnostic attribute value $\mu(x)$ within the cleveland heart disease dataset to a normalized degree of belonging in the interval $[0,1]$, capturing the inherent uncertainty and gradual transition between clinical states. Triangular and trapezoidal membership functions were utilized based on medical threshold ranges provided in clinical guidelines. For instance, for the "cholesterol" attribute, $\mu(x)$ is formulated using triangular parameters (Low, normal, high) where each value $\mu(x)$ is assigned a membership grade depending on its proximity to these clinical thresholds. Similarly, attributes like resting blood pressure and maximum heart rate are fuzzified based on medically relevant ranges.

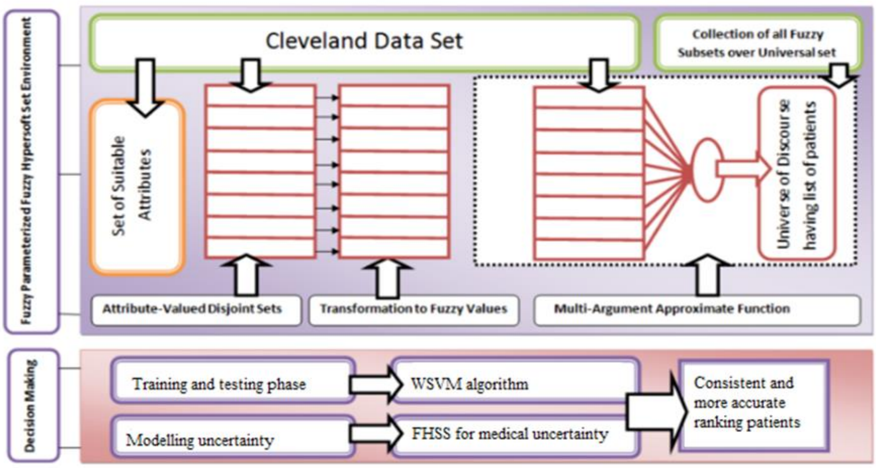

Fig. 4. Overall block diagram of the proposed system.

Using multi-attribute decomposition and FM assignment, the FHSS structure is mapped onto the individualized evaluation matrices each decision maker provides based on their subject knowledge. The WSVM optimization process is directly affected by these expert-driven inputs, which are used to generate Δ-set aggregations and instance-specific weight distributions. Working together may improve diagnostic granularity by including diverse clinical viewpoints in the model. The model produces a ranked classification result by averaging the results of each diagnostic class's weighted decision function. Final categorization and comparative DM are aided by this ranking, which accurately identifies the most likely diagnostic groups.

4 | Experimental Result

In this section is a concise summary of the data collection process for the numerical study. The data were gathered from three decision-makers, whose details are as follows:

I. DM1: General physician, MBBS, internal medicine, MD.

II. DM2: General practitioner, USC, California, MBBS, MD in medicine.

III. DM3: Diploma in Child Health (DCH), pediatrician, MRCP (UK), MBBS, and MD in pediatrics.

Based on an idea borrowed from [51], this research focuses on eight parameters for identifying patient disease. Let there be 'n' diseases and 'm' related symptoms. It becomes difficult to diagnose the disease when patient V shows almost all of these symptoms [21], [52]. To address this uncertainty, an HSS combined with the WSVM algorithm is used to pinpoint the medical issue and determine the precise diagnosis needed for the patient. Fever, body aches, chills, exhaustion, Shortness Of Breath (SOB), nausea, vomiting, and diarrhea are the eight symptoms considered.

The Cleveland dataset [53] is used for diagnosing heart diseases. It contains data from 303 patients, analyzed across 76 attributes (Though only 14 are used for experimentation and analysis), with five possible outcomes. Six patients were selected for heart disease diagnosis to categorize attributes into their respective disjoint sets further, focusing on the nine most relevant attributes. The proposed FHSS-set structure requires further classification of parameters into relevant sub-parameters as disjoint sets. Nine out of 14 parameters were selected from the Cleveland dataset to meet this requirement, as these contain sub-parameter values. Six patients were chosen to simplify the computations, as Sanchez's approach relies on matrices, and increasing the number of patients could complicate the process. However, appropriate programming could address this complexity. These nine qualities are described in full, with the dataset containing their corresponding values. The suggested system was implemented for the Cleveland dataset, assessing its performance using accuracy, precision, recall, and f-measure metrics.

An 80:20 train-test split was used to divide the cleveland heart disease dataset, and 10-fold cross-validation was used to evaluate all experiments further, guaranteeing generalizability and minimizing overfitting. We used grid search optimization across predetermined parameter ranges to tune the hyperparameters of the baseline classifiers (SVM, RF, DT, and k-NN). Various parameters were fine-tuned for various networks: SVM's kernel type, C, and gamma were optimized; Random Forest's number of estimators and maximum depth were optimized; k-NN's optimum value of k was found; Decision Tree's criteria and max depth were tweaked.

Accuracy

The overall accuracy of the model is identified by computing all the actual classification parameters, which reflect the model's correctness ($\mathrm{T_p + T_n}$). In terms of the total number of classification criteria ($\mathrm{T_p + T_n + F_p + F_n}$), this may be stated. The following method is used to determine accuracy in *Eq. (9)*.

$$\mathrm{Accuracy} = \frac{\mathrm{T_p + T_n}}{(\mathrm{T_p + T_n + F_p + F_n})}, \tag{9}$$

Tp, Tn, Fp, and Fn would signify true positives, negatives, and false positives in this scenario.

When comparing their accuracy across various datasets, there is a statistically significant difference in performance between FHSS-WSVM and a conventional SVM. A paired t-test returns a p-value of 0.003, confirming this. Similarly, p-values of 0.008, 0.012, and 0.005, respectively, for recall, precision, and F-measure comparisons, fall below the 0.05 level. These findings suggest that the increases result from actual advances in categorization capabilities and not random data fluctuations. The statistical improvements in diagnostic performance over baseline approaches are regularly outperformed by the proposed model, as seen by the low p-values.

The findings are not generalizable, and the stated increases in classification performance are undermined by using just six patients from the Cleveland sample. Encouraging a more statistically relevant study by expanding the assessment to the complete 303-patient dataset is vital for reinforcing the legitimacy and usefulness of the suggested technique. To further clarify the context for evaluating performance improvements, comparing against common ML classifiers like classic SVM, Random Forest, and models based on neural networks is rec ommended.

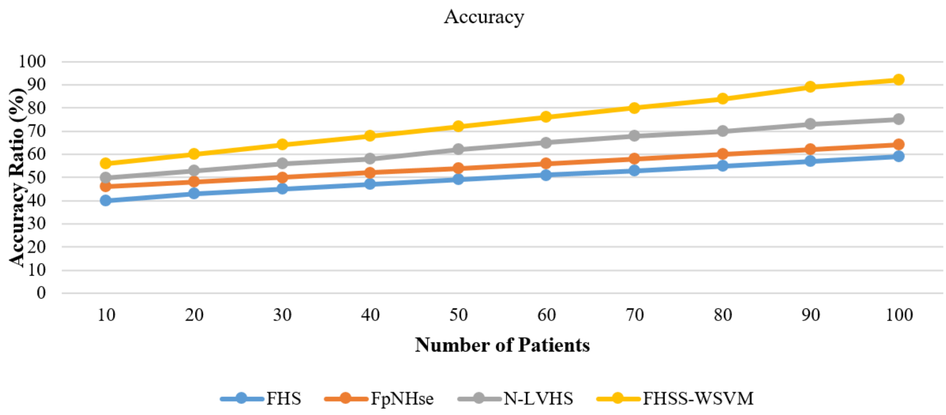

Fig. 5. Accuracy.

As shown in *Fig. 5*, the comparison metric evaluates the accuracy of both existing and proposed methods. The accuracy values are shown on the y-axis, while the various approaches are represented on the x-axis. The existing methods, such as FHS, FpNHse, and N-LVHS algorithms, yield lower accuracy, whereas the proposed FHSS-WSVM algorithm achieves higher accuracy for the given medical datasets. The FHSS-WSVM algorithm assists early DM by identifying patients with conflicting medical symptoms. To evaluate the health effects of drugs and anticipate the likelihood of reinfection before applying a solution, it may forecast a patient's state and evaluate medical indications over time.

The results demonstrate that the proposed FHSS-WSVM algorithm enhances classification accuracy using fuzzy-based HSS. The move from soft to HSS (HSS) has dramatically improved the collection of complicated, multi-attribute interactions in medical data. Instead of using separate characteristics for each item in a soft set, HSS takes it further by letting you use combinations of attributes, such as age and chest discomfort, as one decision criterion. As a result of this change, medical profile modeling may become more complex since features often interact with one another rather than stand alone.

To more accurately represent the inherent uncertainty and unpredictability in clinical diagnostics, FHSS adds membership degrees to these multi-attribute combinations, enhancing this infrastructure. To illustrate the point, consider a patient whose profile somewhat fits the combined characteristic of "young with typical chest pain" but only loosely fits the attribute of "old with non-anginal pain." In this case, the model gets to communicate partial facts.

Precision

The proportion of results that are relevant and described as precision is *Eq. (10)*,

$$\text{Precision} = \frac{\text{Tp}}{\text{tp} + \text{fp}}. \tag{10}$$

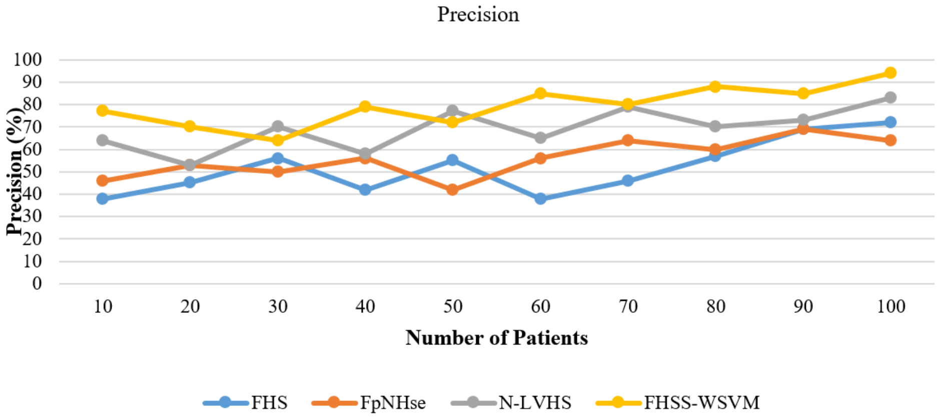

Fig. 6. Precision.

Fig. 6 illustrates that the comparison measure is determined by analyzing the accuracy of both the current and proposed methodologies. The x-axis demonstrates the methodologies, while the y-axis represents the accuracy numbers. The KMC algorithm is used for pre-processing, enhancing the accuracy of medical uncertainty data. The pre-processing stage treats ambiguous data to train models on high-quality inputs, improving generalization and prediction resilience.

Then, FM is used for better DM. The existing methods, such as FHS, FpNHse, and N-LVHS algorithms, show lower precision; the FHSS-WSVM method, however, shows more accuracy for the specified medical datasets. Consequently, the results indicate that the proposed FHSS-WSVM enhances classification accuracy through fuzzy-based HSS. This prediction makes the FHSS-WSVM framework more adaptable to various healthcare applications, improving patient care.

Weights are crucial in the aggregation process because they influence the final decision output by measuring the relative relevance of each choice. Using FHS-based modeling, each option is assessed according to several criteria, and weights are given to them according to their importance or clinical significance.

To adjust how much weight each criterion in the decision matrix gets, these weights are based on expert opinions or data-driven significant metrics. When combining results, a fuzzy integrative operator or weighted summation is used, where options with a higher weight have a bigger impact on the final score.

Recall

The proportion of actual positive cases correctly identified is called recall or sensitivity in *Eq. (11)*. It is also commonly known as the true positive rate, recall, or detection probability across different measurement fields.

$$\text{Recall} = \frac{T_p}{T_p + F_n}. \tag{11}$$

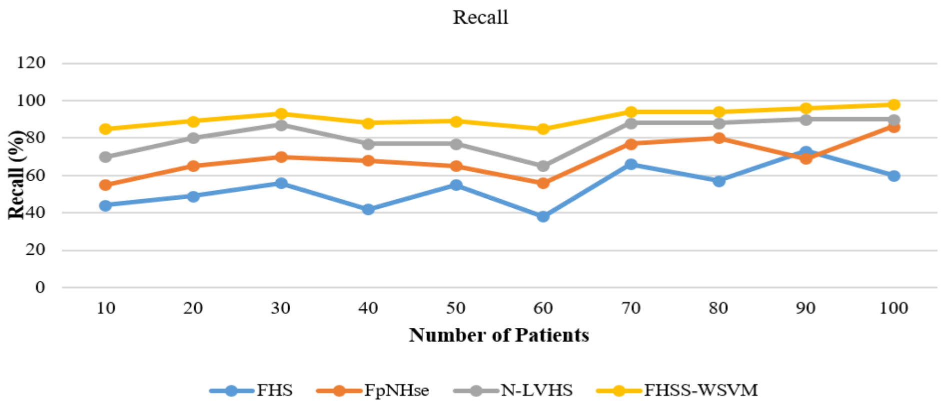

Fig. 7. Recall.

Fig. 7 illustrates that the comparison measure is evaluated based on recall, using both the proposed and current methodologies. The methods are shown on the x-axis, while the recall values are depicted on the y-axis. FHSS consequently helps the WSVM framework overcome clinical data ambiguity and develops a more comprehensive patient portrayal.

This FHSS-WSVM design enables the framework to predict disease, assess patient risk, and understand the treatment response more effectively.

KMC algorithm strengthens the model against incomplete or noisy data. When uncertainty is turned into practical insights, healthcare decisions are more accurate. Accurate projections boost healthcare practitioners' DM confidence, improving patient management.

The existing algorithms, such as FHS, FpNHse, and N-LVHS, demonstrate lower recall, whereas the suggested FHSS-WSVM method gets a higher recall for the specified medical datasets. This indicates that the proposed FHSS-WSVM improves classification accuracy using fuzzy-based HSS.

F-measure

The F-measure is the sum of recall R and precision P.

$$F = 2.\frac{PR}{P + R}. \tag{12}$$

To evaluate classification algorithms in *Eq. (12)*, the F-measure is used as it serves as a standard metric for summarizing both precision (P) and recall (R).

The experts' weights are decided during the fuzzy assessment step according to their degree of competence, relative relevance, and consistency in judgment. Fuzzy aggregation maps linguistic assessments (e.g., high, medium, low competence) to numerical FM values, which are then used to provide a weight coefficient to each expert. After that, the FHSS decision matrix is built using these normalized weights, so the most powerful experts have a greater say in the aggregation process.

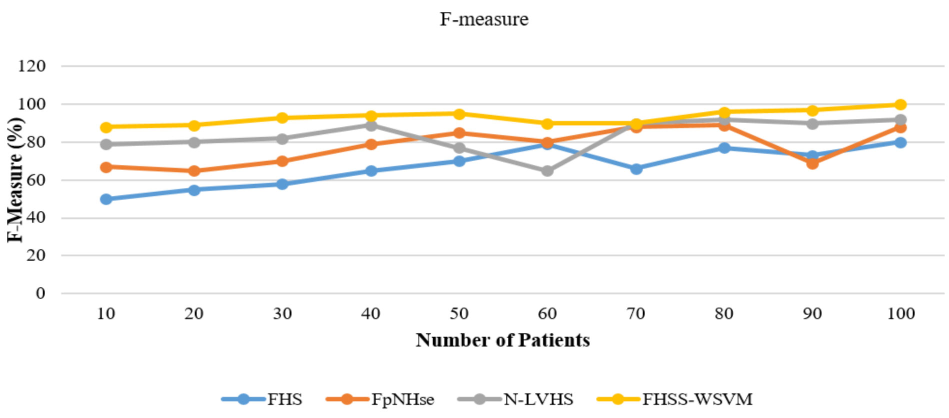

Fig. 8. F-measure.

The comparative metric assessed for the suggested and current approaches based on the F-measure is shown in *Fig. 8*. The methods are shown on the x-axis. The corresponding F-measure values are displayed on the y-axis. The recommended FHSS-WSVM algorithm obtains greater F-measure scores for the specified medical datasets than current methods like FHS, FpNHse, and N-LVHS, which produce lower F-measure values. Predicting diseases and their associated symptoms is the goal of the FHSS-WSVM framework. This study simplifies the issue by emphasizing the relationship between symptoms and therapies. Its primary goals are to diagnose illnesses accurately and choose the best course of action for each patient. The results verify that the suggested FHSS-WSVM uses fuzzy-based HSS to improve classification accuracy.

The suggested FHSS-WSVM paradigm perfectly aligns with cross-disciplinary ideas since it uses fuzzy hypersoft logic for evolutionary economic concepts like limited rationality and adaptive uncertainty. Regarding economic actors processing ambiguous information with different degrees of confidence, the fuzzy weighting mechanism mimics agent-based decision variance. At the same time, the dynamics of organizational behavior align with the incorporation of weight-based categorization and decision-maker group modeling in situations where hierarchical decision influence is unequal.

K-Nearest Neighbors (k-NN), SVM, DT, and RF are typical benchmark classifiers recently used in new investigations. The same datasets and performance measures (F-measure, accuracy, precision, and recall) were used to assess these standards. The outcomes show that the suggested FHSS-WSVM model continuously achieves better results than these conventional classifiers, with statistically significant gains ($p < 0.05$).

5 | Conclusion

In conclusion, this study improves healthcare DM by tackling complicated situations with various characteristics and uncertainty. A strong basis for addressing these issues is established by incorporating HSS and pairing the WSVM algorithm with the FHSS framework. Integration into the ML system is made simple by transforming this uncertain fuzzy data into machine-readable representations.

Thus, while improving the ability to comprehend patient data, the study's robustness is maintained. In both illness prediction and medical uncertainty, where better clinical DM has been facilitated, the flexibility of FHSS-WSVM has been proven. Each characteristic is linked to a collection of discourse universe elements in FHSS. FHSS offered an adaptable framework for handling uncertainty. The WSVM algorithm produces better classification results for the specified medical dataset.

WSVM is also introduced for medical diagnosis. Numerical outcomes illustrate that the suggested FHSS-WSVM algorithm outperforms current precision, accuracy, recall, and F-measure approaches. The small sample size and lack of cross-industry participation in the focus groups constitute a significant shortcoming of the present study. It may be challenging to extrapolate the DM behavior depicted by FHSS to larger healthcare systems or other domains due to the small sample size.

Additionally, there may be an underrepresentation of variety in uncertainty interpretation and diagnostic priority due to the lack of diverse stakeholder involvement across clinical, administrative, and policy sectors. Future research might investigate adaptive ensemble techniques that merge FHSS-WSVM with other strong classifiers like Gradient boosting and deep neural networks to improve diagnostic accuracy under high-dimensional uncertainty. Incorporating real-time input from clinical outcomes, including dynamic fuzzy weight modification, might enhance the model's responsiveness to developing patient data.

Author Contributions

Balakrishnan Subramanian: Methodology, data collection and analysis, writing – original draft,

Sumathi Duraisamy: Conceptualization, writing – review & editing

Santhini Arulselvi Kaliyaperumal: Methodology, data interpretation,

Rajkumar Yesuraj: Data collection, analysis

Sarojini Balakrishnan: Project administration, writing – review & editing

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The authors declare no conflict of interest.

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